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# Agent-based simulation of affordance-based human behaviors in emergency evacuation

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ABSTRACT

Complex cognitive processes corresponding to human control behaviors cannot be easily inferred using (1) a logical rule-based model, (2) a statistical model, or (3) an analytical predictive model. Predicting human behaviors in complex and uncertain environments like emergency evacuation is considered almost impossible (at least NP hard) in systems theory. In this paper, we explore simulating human behaviors using affordance-based finite state automata (FSA) modeling, based on the ecological concept of affordance theory. To this end, we introduce the conceptual and generic framework of affordance-based human behavior simulation developed through our previous work. Following the generic framework, formal simulation models of affordance-based human behaviors are developed, especially for emergency evacuation, to mimic perception-based dynamic human actions interacting with emergent environmental changes, such as fire. A "warehouse fire evacuation" case is used to demonstrate the applicability of the proposed framework. The human action planning algorithms in the simulation model are developed and implemented using the Adjusted Floor Field Indicators, which represent not only the evacuee's prior knowledge of the floor layout but the perceivable information about dynamic environmental changes. The results of our simulation study verify that the proposed framework accurately simulates human fire evacuation behavior. The proposed framework is expected to capture the natural manner in which humans behave in emergency evacuation and enhance the simulation fidelity of analyses and predictions of perceptual human behaviors/responses in the systems by incorporating cognitive intent into human behavior simulations.



## 1. Introduction

Recently, the need to observe, analyze, and predict human behaviors using computer simulation technologies has emerged in public and social system design, where humans and their inherent capabilities have eluded formal analysis. For example, in a terrorism-driven evacuation situation, a fire, or a natural disaster such as The station nightclub fire in 2003 [1] (the fourth deadliest nightclub fire in American history, killing around 100 people), understanding and predicting how a human will respond (or, more properly, how a crowd of humans will respond) within certain circumstances will allow

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law enforcement agencies to be better prepared and will greatly reduce the damage associated with these disasters. However, the cost of holding practical experiments is prohibitive, and the experimental data are difficult to capture [2].

Unlike traditional physical systems, from which humans are excluded, research on modeling and simulating human behaviors in human-environment complex systems has been slow due to the challenges associated with the nondeterministic and dynamic nature of the human action/decision making processes. The cognitive processes in human behaviors cannot be described simply using logical rule-based models, since predicting human behaviors under uncertainty is a highly complex systems problem [3].

While systems theory has grown rapidly, the modeling and simulation of human-environment systems that accommodate both human cognitive models and discrete system representations have not kept pace. This is especially true for discrete event-based systems, which comprise the best computational modeling methods of predicting physical system behaviors, as they can model event occurrences and changes of system states in either a deterministic or stochastic manner [4]. However, this is not so for human-environs, in which both discrete and continuous characteristics exist together, creating a major modeling void, given that most complex systems of interest to modern society are composed of human activities.

To overcome the challenge of addressing the human in systems, we start our discussion on the premise that perception guides a human's actions towards his or her goal. To this end, two related hypotheses regarding cognitive human actions are employed: (1) humans use perception-based actions in an ecological environment [5,6] and (2) humans utilize goal-directed actions through prospective control [7]. The former supposes that a human makes a decision to take an action based on the perceived information he or she takes from the environment. An ecological understanding of perception-based human actions in animal-environment systems was initiated by Gibson in 1979 [5]. He defines an affordance as "a property of the environment that provides an action opportunity offered to an animal (human), either for its good or ill." According to him, a human action is regarded as a consequence of direct perception of affordance and effectivity (an individual's ability to take a specific action). Thus, a human makes decisions to take action based on perceived information regarding sets of affordance–effectivity. On the other hand, the latter assumes that every human action has its own objectives or intentions for prospective control (i.e., the projection of control into the future); thus, every future human action can be interpreted as an intermediate goal to be realized to reach a final goal in the future, and a human makes a plan (a series of actions) to achieve the goal and anticipates the perceptually available outcomes and opportunities to take the series of actions that advance the plan.

From the viewpoint of systems theory, there are two kinds of approaches to modeling human behaviors: the experimental modeling approach and the formal modeling approach. The former method builds a model using an experimental monitoring of human behaviors through human-in-the-loop simulation [8]. This approach is seen as lacking in generality and completeness of experimental results due to its simplified and controlled laboratory conditions [14]. On the other hand, the latter is an attempt to represent the qualitative and dynamic nature of nondeterministic perception-based human behaviors using quantitative formal models. Kim et al. have advocated affordance-based descriptive formalism for modeling complex human-environment systems [9,10]. Formalism describes a system as a set of discrete states and regards the transitions between states as triggered by certain human actions leading to the next states in the computable models. In our previous conceptual investigation of the overall system architecture and generic functional components of an affordance-based simulator, we employed the modeling formalism of Kim et al. as the basis of our formal scheme [11].

The objective of this paper is to develop and verify an agent-based formal simulation framework of affordance-based human behaviors in emergency evacuation situations using formal modeling methods. We formalize perception-based human evacuation behaviors into a simulation model via the affordance-based FSA model, agent models, and a human action plan. Specifically, an algorithm of human behavior logic is presented. Using this algorithm, each human agent establishes and schedules a series of actions based on the dynamic perceptual properties of affordance and effectivity to reach the goal state. The proposed simulation framework is illustrated using a Warehouse Fire Evacuation (WFE) problem. The simulation results of a few different scenarios are studied to demonstrate the model's capacity to solve the considered problem.

When modeling and simulating human behaviors, other human attributes (such as emotions, cultures, knowledge levels, and social factors) need to be considered along with the perceptual properties. In particular, social factors such as interactions and communications within and between groups of people should be considered in human behavioral simulation models, especially in the case of an emergency evacuation [12,13]. In this research, however, our perspective on human behavior at this stage is limited to individual decision making with human perceptions rather than more complex problem domains involving human interactions and communication. Thus, only limited communication among human agents within their perceivable (or communicable) ranges is considered in the presented simulation framework. Other human attributes, such as crowd psychology and swarm intelligence, will be considered more specifically in the future. The framework and simulation models proposed in this paper will provide a predictive analysis capability for the design of human-involved systems, especially for emergency evacuation design and control.

The remainder of this paper is organized as follows: Section 2 provides the related work and background of this research. Section 3 reviews the overall system architecture of affordance-based human behavioral simulation. Section 4 presents a formal simulation framework of affordance-based human behaviors using the WFE problem. We demonstrate the applicability of the proposed framework and the capability of the simulation models by running a fire evacuation scenario in Section 5. Finally, we conclude this paper with a discussion of possible directions for future research in Section 6.

## 2. Background

### 2.1. Human behavioral modeling

Human decision behaviors have been studied by researchers in various disciplines, such as artificial intelligence, psychology, cognitive science, and decision science [14]. Lee et al. [14] classified human decision behavior models into three major categories based upon their theoretical approach: (1) an economics-based approach, (2) a psychology-based approach, and (3) a synthetic engineering-based approach. Each approach exhibits strengths and limitations. Models employing the economics-based approach have a concrete foundation, based largely on the assumption that decision makers are rational [15,16]. However, they are unable to represent the nature of human cognition. To overcome this limitation, models using a psychology-based approach have been proposed [17,18]. While these models explicitly account for human cognition, they generally address human behaviors only under simplified and controlled laboratory conditions [19]. Finally, synthetic engineering-based models try to effectively integrate the engineering-, psychology-, and economics-based models to represent human behaviors in complex and realistic environments [14,20–24]. Soar, Act-R, and Belief-Desire-Intention (BDI) are three popular synthetic engineering-based models. Soar and Act-R have their theoretical bases in the unified theories of cognition [23], an effort to integrate research from various disciplines to describe a single human cognition. On the other hand, the BDI paradigm, which divides human mental states into three components—beliefs, desires, and intentions—allows the use of a programming language to describe human reasoning and actions in everyday life [24]. However, it lacks a scientific basis because it is based on folk psychology. Furthermore, none of these uses the concept of direct perception, which produces immediate human actions with reference to dynamic environments.

### 2.2. Affordance theory and perception-based human action

Gibson first defined the affordances of the environment as what it offers to the animal (or person) and what it provides or furnishes, either for good or ill [5]. Since Gibson proposed his definition, the notion of affordance has been further refined and theorized. For example, Turvey presents a perspective on the ecological ontology of affordances with links to prospective control [7]. He frames his definition of affordance in terms of the properties representing a potential state not currently realized (called "dispositional properties" or "dispositions"). Dispositions occur in pairs in which a property of the environment (i.e., the walk on-ability for the person) is complemented by a property of the animal's capability, known as an effectivity (i.e., the ability to walk on the stairs' surface). The terms of affordance and effectivity can thus be combined to incur the activation of a different property (i.e., climbing the stairs) [7]. Specifically, Turvey mathematically presents a formal definition of affordances using a juxtaposition function, as follows:

Let $W_{pq} = j(X_p,Z_q)$ be a function composed of an environmental object ($X$) and an animal ($Z$), and let $p$ and $q$ be properties of $X$ and $Z$, respectively. Then, $p$ refers to an affordance of $X$ and $q$ is the effectivity of $Z$, if and only if there exists a third property $r$ such that:

(i) $W_{pq} = j(X_p,Z_q)$ possesses $r$,
(ii) $W_{pq} = j(X_p,Z_q)$ possesses neither $p$ nor $q$, and
(iii) Neither $X$ nor $Z$ possesses $r$, where $r$ is a joining or juxtaposition function.

For example, in the case of a person-climbing-stairs system ($W$), a person ($Z$) can walk ($q$), stairs ($X$) can support something ($p$), and they together yield climbing property ($r$). This formal definition of the affordance, effectivity, and juxtaposition functions can be mapped to the precondition set of state transition function in the FSA and provides a foundation upon which the concept of an affordance can be combined with software engineering and systems theory. The concept of affordance and effectivity in human-environmental systems enables us to represent immediate human actions, heretofore considered within the realm of ecological psychology, within formal system representation.

### 2.3. Affordance-based formal modeling of perception-based human action

The affordance-based modeling approach has been widely adapted for designing robot controls and mimicking human actions in specific environmental situations [25]. However, most of these efforts lack formal ways to model human actions with respect to system transitions, due to the low level of abstraction in modeling perceptual properties. Recently, Thiruvengada and Rothrock have developed a computational model of Gibson's affordance theory based on Colored Petri Nets (CPN) [26]. By considering the context of the highway-exit space problem, affordance and effectivities in the model are represented by the presence of tokens within each lane node of the highway lane CPN model and the tokens with colors corresponding to each driver within the driver CPN model, respectively. Similarly, Kim et al. have suggested an affordance-based descriptive formalism for complex human-involved systems using finite state automata [9,10]. In their work, an environmental system is defined as a set of nodes and arcs that describe discrete states of the system and the transitions between states, respectively. Then, a set of transitions between states is triggered by certain human actions to lead to the next states. Affordance–effectivity combinations are considered as preconditions for actualizing possible human actions. The formalism provides a systematic way to include physical preconditions of human action possibilities within computable modeling methodologies. In this paper, we intend to model perception-based human actions into the framework of human-behavioral simulation in order to analyze human behavioral patterns within complex systems.

### *2.4. Agent-based simulation of human behavior*

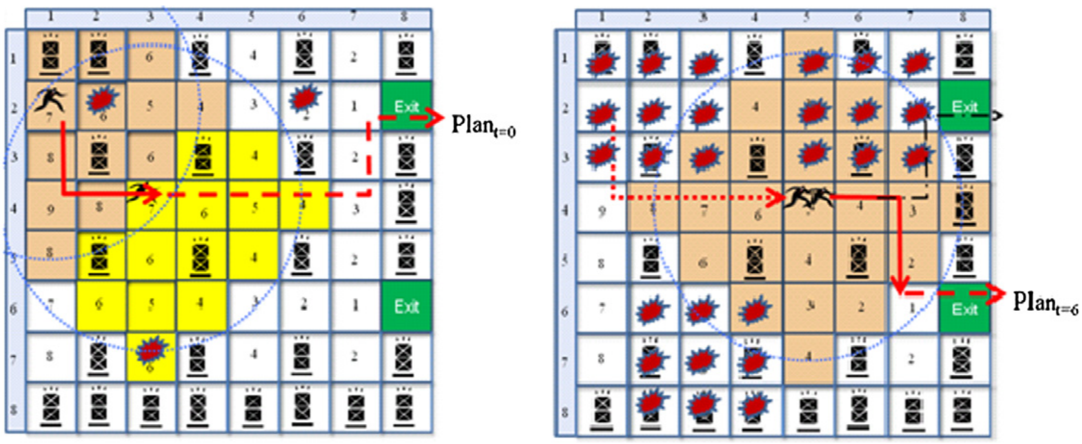
Santos and Aguirre [13] have reviewed human behavior simulation techniques including (1) flow-based, (2) cellular automata, and (3) agent-based models in emergency evacuation areas (a scenario considered in this paper) comprehensively. Flow-based approaches that model the density of nodes in continuous flows enable the user to construct a simulated physical environment as a network of nodes [27]. Cellular automata models discretize space and model the node density in individual floor cells. In this model, the evacuees are modeled as individuals on a grid [28] (AEA Technology, 2002).

In agent-based modeling, a flexible set of attributes is assigned to each person, so that an intelligent agent mimics the abstract characteristics of a human. The intelligent agent has several capabilities, such as autonomy, social ability, reactivity, pro-activity, cooperation, learning, and adaptivity [30]. Raubal suggests a perceptual way-finding model that integrates simulated environmental states and agent beliefs within a "Sense-Plan-Act" framework. In the simulation, a cognizing agent is used to mimic people's way-finding in unfamiliar buildings based on knowledge gained through their visual perception of sign information and affordances at each decision point while reaching the goal [31]. Shendarkar et al. propose the use of an agent-based simulation modeling paradigm to construct a crowd simulation [32]. They use the BDI agents driven by the human behavior data extracted from the VR experiments to demonstrate the simulation of crowd evacuation management during terrorist bomb attacks in public areas. Evacuation models such as Egress, Building Exodus, Simulex, Exit, and Wayout can be used to simulate the evacuation efficiency of buildings [33]. Building Exodus and Simulex, widely used as commercial software for evacuation simulations, assume the presence of a rational agent able to assess the optimal escape route and avoid static physical obstructions [34,35]. However, none of them is grounded on both the ecological concept of affordance and a formal system that enables individual decision making based on human perceptions of dynamic environmental elements for the simulation.

## 3. Simulation framework of affordance-based human behaviors in emergency evacuation

### *3.1. Scenario: Warehouse Fire Evacuation (WFE) problem*

To develop a formal simulation framework of affordance-based human behaviors in an emergency evacuation, the Warehouse Fire Evacuation (WFE) problem is explored. In this WFE Problem (see Fig. 1a), a fire breaks out in a warehouse where two human operators are working. The warehouse area is equally divided into a rectangular grid of $0.8 \times 0.8\ m^2$, used for either storage or as a passageway. In this storage area, goods are stacked up so high that operators cannot see over the storing lots. Fires break out at three different locations in the warehouse and are quickly propagated to neighboring lots at a certain speed, as shown in Fig. 1. As soon as an operator perceives the fire, he/she shall have to find a safe and feasible route to an exit along a passageway by considering the perceived surrounding situations in order to escape from the fires. When he/she tries to move to the next passageway lot, if the lot is already occupied with a fire, he/she cannot access it and must find another passageway that offers an affordance to move. The following assumptions are made to simplify the problem:




(a) at time $t_0$ (b) at time $t_6$

**Fig. 1.** Example of warehouse fire evacuation.

(i) Each evacuee can perceive the situations at a 360° viewing angle in the warehouse.
(ii) An evacuee can move to the next lot only in the front and back directions or to the right and left at right angles. He/she cannot move diagonally in the warehouse.
(iii) Each evacuee acts independently of the others, but some interactions are possible among evacuees to share information and knowledge about the floor layout or the current situation in the warehouse.
(iv) Interactions among evacuees can occur only when they are located within the others' perceivable boundary on the floor.
(v) Only fire is considered as a dynamic environmental element (smoke and heat are excluded).

### 3.2. Overall system architecture of affordance-based human behavioral simulation

In this section, the system architecture and generic functional components of the affordance-based human behavioral simulation are briefly overviewed [11]. The proposed affordance-based simulation framework can evaluate action possibilities and predict human behaviors using the embedded formal automata models of human-involved systems. It considers both affordance and effectivity as dynamic control parameters triggering human actions in the simulation to deal with the interactions between human and dynamic environmental elements.

Fig. 2 depicts the system architecture of the proposed affordance-based simulator, whose four major components are the (1) Affordance-based FSA model, (2) Agent Models, (3) Event Generator, and (4) Human Action Planner. The affordance-based FSA is the core module of the simulation. The affordance-based FSA models are formal automata models of human-involved systems describing the whole state map (including a goal state), which can be transited by human actions and environmental dynamics in the system. The FSA model provides dynamic (temporal and spatial) situations and the preconditions of possible transitions for agents in the system.

While the affordance-based FSA model is a descriptive model for representing a system, the event generator generates each event to drive the FSA model according to the dynamically changing situation. It schedules future events based on system dynamics. In order to drive the FSA model, the event generator triggers each event by receiving perceived affordances and effectivities from human agents according to pre-defined human action plans.

### 3.3. Formal representation of the WFE system using affordance-based FSA

Based on the modeling hierarchy and dynamic properties of the system, we can define an affordance-based FSA for representing evacuee movement from current to adjacent lots in the generalized evacuation space, as shown in Fig. 3. The mathematical representation of the FSA model is defined as a 6-tuple FSA, as follows:

$M_{comb} = \langle \Sigma, S, s_0, M_{atom}, \delta_{ext}, F \rangle$, and
$M_{atom} = \langle \{X, Z, W\}, \{P, Q, PA\}, \Pr, j, \pi, ta, \delta_{int}, t_{int} \rangle$:

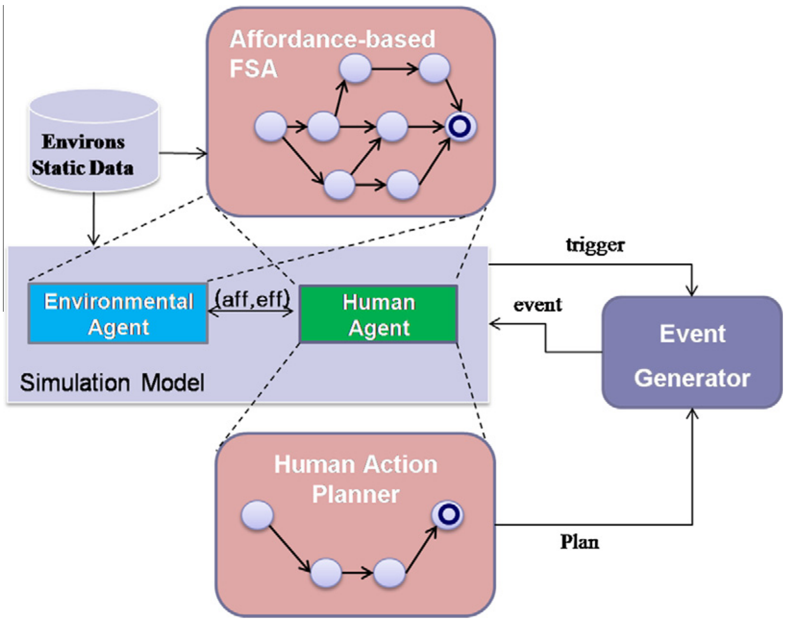



**Fig. 2.** System architecture of the proposed affordance-based human behavior simulator [11].

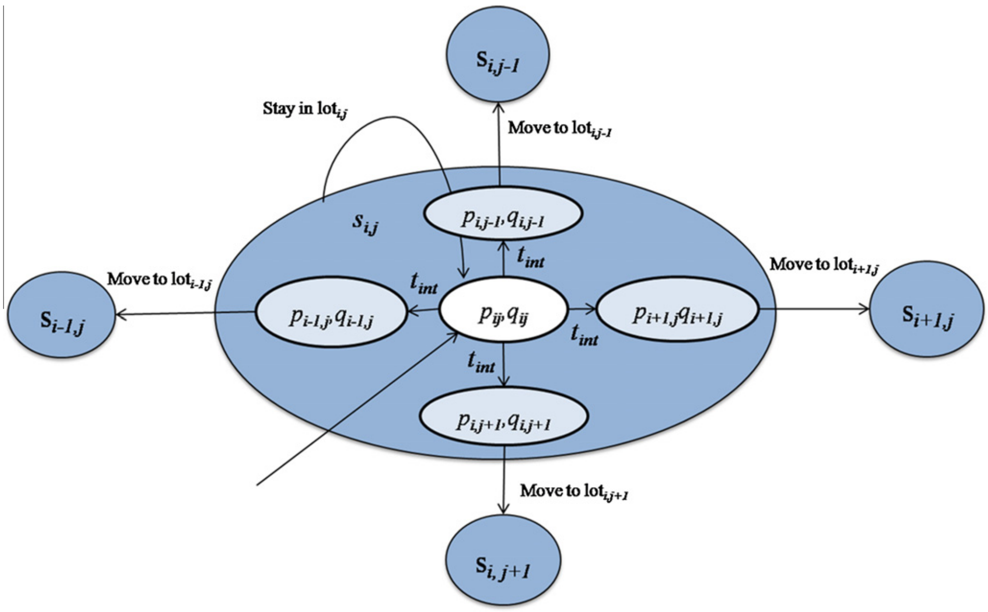



**Fig. 3.** Affordance-based FSA of evacuation behaviors in the WFE system.

$\delta$: $S \times \Sigma \rightarrow S$,
Pr: $X_p \rightarrow P$, Pr: $Z_q \rightarrow Q$, Pr: $W_{pq} \rightarrow PA$
$j$: $X_p \times Z_q \rightarrow W_{pq}$, $\pi$: $P \times Q \times C \rightarrow PA$, and
$\delta_{int}$: $\{P,Q\} \times t_{int} \rightarrow \{P,Q\}$, where;
$\Sigma$: Set of transitions among system states,
$S = \{s_{ij}$ = an evacuee is on the $\text{lot}_{ij}$, $i = 1, \ldots, 8$, $j = 1, \ldots, 8\}$,
$F = \{s_{28}$ = exit 1, $s_{68}$ = exit 2$\}$.
$j$: Juxtaposition function,
$\delta_{ext}$: System state (external) transition function,
$\delta_{int}$: Time advance (internal) transition function,
Pr: Perceptual predicate function,
$\pi$: Possible action generation function,
$X$: A warehouse under fire,
$Z$: An operator working in the warehouse,
$W$: System of evacuation from warehouse fire,
$P = \{p_{ij}$ = move-ability to the $\text{lot}_{ij}$, $i = 1, \ldots, 8$, $j = 1, \ldots, 8\}$,
$Q = \{q_{ij}$ = 'evacuee's capability to move to the $\text{lot}_{ij}$, $i = 1, \ldots, 8$, $j = 1, \ldots, 8\}$,
$C = \{c_1$: no fire on the next lot, $c_2$: emptiness of the next lot, $c_3$: no barriers between the current and next lot$\}$,
$PA = \{(\text{go to lot}_{ij})$, $i = 1, \ldots, 8$, $j = 1, \ldots, 8\}$,
$ta$: Target action, $ta$ $PA$ and $ta$ a
$t_{int}$: time advance function.

The considered FSA model consists of sets of system states, internal states, external transitions, and internal transitions (see Fig. 3). The model presents five different system states: "evacuee is on the current lot ($S_{ij}$)," "evacuee is on the east adjacent lot ($S_{i+1,j}$)," "evacuee is on the north adjacent lot ($S_{i,j-1}$)," "evacuee is on the west adjacent lot ($S_{i-1,j}$)," and "evacuee is on the south adjacent lot ($S_{i,j+1}$)." Each system state contains multiple internal sub-states that include pairs of affordance ($p_{ij}$: move-ability to the $\text{lot}_{ij}$) and effectivity ($q_j$: evacuee's capability to move to the $\text{lot}_{ij}$) as preconditions for external transitions in the system. An external state transition can produce physical changes in the system state caused by a specific human movement in the WFE system. On the other hand, the internal state transition is concerned with a precondition(s) that must be satisfied to actuate the external state transition in the system. It connects two sub-states, each a combination of a specific affordance and effectivity. If a certain precondition of $p_{ij}$ and $q_{ij}$ existence is satisfied, an evacuee can move to one of the adjacent lots until it reaches the final system state of "exits" in the space. The $p_{ij}$ and $q_{ij}$ states are determined by the warehouse layout and the states of the environmental agents (e.g., the fire). These affordances and effectivities are time-varying properties determined by the physical situations of the environmental elements and human capabilities. Thus, let us assume the initial states of affordance and effectivity in the current lot are $p^*$ and $q^*$, respectively. In a certain amount of time, $t_{int}$, if the current status of affordances and effectivities ($p_i, q_j$) may be changed to the combination ($p_m, q_n$) ({$m$ = 1,2,3,4}, {$n$ = 1,2,3,4}) to meet specific action conditions, the juxtaposition function $j$ then generates a set of possible actions, $PA$, based on the action conditions (for example, if only the action conditions to the north and east adjacent lots are satisfied, the possible actions are $PA$ = {'go north', 'go east'}). To take a specific action among $PA$, three physical action conditions $C$ should be satisfied, including "$c_1$: no fire on the next lot," "$c_2$: emptiness of the next lot," and "$c_3$: no barriers between the current and next lot." If an evacuee takes a specific action screened by the filtering process, an external state transition will then occur, and a physical system state will go to the next one.

## 4. Human agent model for affordance-based evacuation simulation

It should be noted that humans are assumed to utilize goal-directed actions through prospective control. In order to achieve his or her objectives or intentions, a human anticipates perceptually available opportunities and series of actions to make a plan. Given this prospective control, a human agent should be designed to act based on a pre-defined plan and through emergent decision making via the perceptual juxtaposition processes of affordances and effectivities.

### 4.1. Agent models in the evacuation simulation

The concept of agent can vary according to its application area. In software engineering, the most widely accepted definition of the agent model holds that the agent is a computer system situated in an environment and capable of autonomous action to meet system objectives [36]. An agent in a simulation model implies a nature for each entity and expresses the complex interaction with other agents in the environment so that the simple agent rule can generate complex system behaviors. While a human agent model is represented by goals, perception abilities, a decision making algorithm, and action capabilities, an environmental agent maps the dynamics of environmental elements onto the system model. Several attributes (e.g., type, name, moving speed, etc.) and the characteristics of each agent are defined to reflect the diversity of the humans and environmental elements in the system. A conceptual model is developed to illustrate the functional procedures of and interactions between the human agent and the environmental agent, as in Fig. 4. It is noteworthy that human actions are affected by the information on affordances and effectivities perceived in the human-environment system.

When the simulation is initialized by a fire in the warehouse, every human agent in the simulation model who perceives the fire within its perceivable boundary is activated to start the evacuation process. Before human agents start to move to their adjacent cells toward the exits, action conditions are checked to see whether the affordance–effectivity dual of the emptiness of the cell and the move-ability to the cell is satisfied. Through these iterative processes of affordance-based simulation, each human agent can proceed to the goal according to its plan. In dynamic situations, they may need to change their plans and goals based on the human-environmental system conditions in the PB. In an unexpected situation (e.g., the planned route is blocked by fire), the human agent should immediately generate alternative plans to reach the goal (i.e., to exit properly).

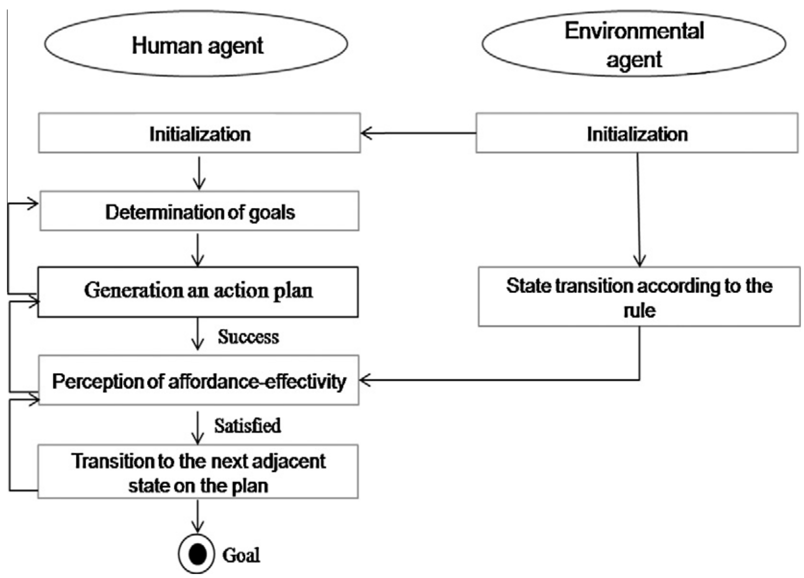



**Fig. 4.** Conceptual model of human agent and environmental agent [11].

### 4.2. Perceivable boundary

Visual information is considered the major source of perception-based action because the visual channel processes dynamic information containing three dimensional optical flows. Therefore, to model human actions driven by perception-based decisions, modeling visual perception ranges is critical, so that the prospective properties of human actions may be combined into the system space.

Considering perception-based actions and planning, we need to define the perceivable boundary (PB) as a horizontal space within which a human can visually perceive the surrounding situation. Since a perceivable boundary is determined by the person's position and the dynamics of other environmental conditions (such as lighting and fog), it should be continuously updated according to the person's movements. Fig. 5 depicts an ideal perceivable boundary. While the shape and range of a perceivable boundary are dependent on the human's visual direction, it is assumed in this example that human agents can enjoy a 360° viewing angle by rotating their body and head of their own volition. So, in this paper, we set a PB as a circle with center point of agent's current position or the cells within the circle as shown in Fig. 5.

### 4.3. Human action plan

The human action planner shown in Fig. 2 generates a feasible sequence of action reaching from the current to the goal state for a human agent. Unexpected or undesired situations occurring within the system cause a transition leading to a deviation from the active plan. If this happens, the planner immediately recalculates the plan to cope with the dynamic change in the environment. The plan is generated based on not only the static information flowing from human knowledge of the surface layout of an environment but also the perception of the dynamic information occurring within the perceivable boundary obtained at the very moment of the planning (or re-planning) and decision making. In this paper, the static information is defined as the Static Floor Field Indicator (SFFI), a set of numbers indicating the distance to the exit [29], whereas the dynamic information is the Dynamic Floor Field Indicator (DFFI), a set of numbers representing the affordances (the human move-abilities) of the perceived areas within the perceivable boundary.

For the simulation's static information, it is assumed that a human has previous knowledge of the floor layout regardless of his or her perception of the environment, enabling a complete plan that persists until the goal is achieved. He or she is supposed to know how far the goal position (i.e., the exit) is from his or her current position in the layout. In dynamic and complex situations that can change the floor layout, however, this is not the case. Suppose the evacuation route needs to be changed because of a fire in a corridor along the evacuee's original evacuation route. If the system is too large for a person to perceive its entirety, he or she cannot know every detail of the current environmental situation beyond his or her PB. The evacuee with insufficient environmental information can make his or her evacuation plan only within the perceivable boundary. Beyond that, he or she may be able to make a rough plan using the layout information in his or her memory. A "rough plan" here means a plan made only with prior knowledge of the layout (static information). On the other hand, a detailed plan is made based on both the static information (prior knowledge) and the dynamic information (perceptual properties) within the perceivable boundary. The planner generates and updates both types of plans when needed (e.g., when an unexpected situation blocking the planned path occurs). Fig. 6 depicts the evolution of human action planning according to human movement (and thus the perceivable boundary).

In the WFE problem, the ranges of the perceivable boundary can be defined by considering each agent's perception capabilities under specific environments (e.g., visibility, intensity of illumination, and loudness). To develop an accurate simulation model, empirical studies will be needed to capture human perceptual properties and perceivable ranges for use in the models. In the evacuation example, each cell in the floor layout is assigned with a Static Floor Field Indicator (SFFI), a grid distance from the cell to the exits. Nearer the exit, lower values correspond to cells. For example, if a cell is located at a distance of 10 grids from the exit, its SFFI will be assigned a 10. The SFFI can be formally represented as *Ns* (distance from exits); it shows the evacuees the way to the exit, since they always prefer to move toward a cell with a value lower than the current

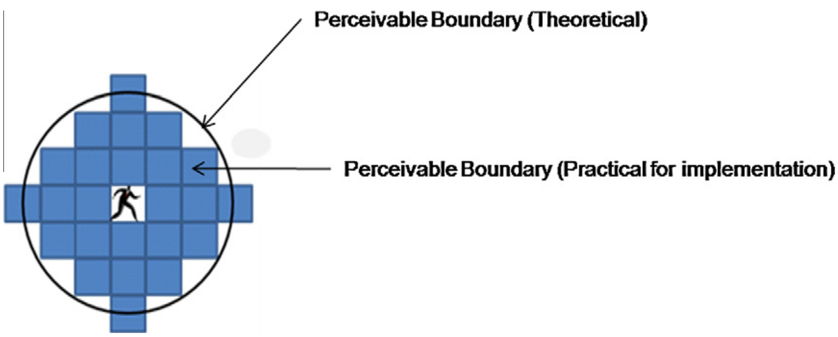



**Fig. 5.** An example of a perceivable boundary.

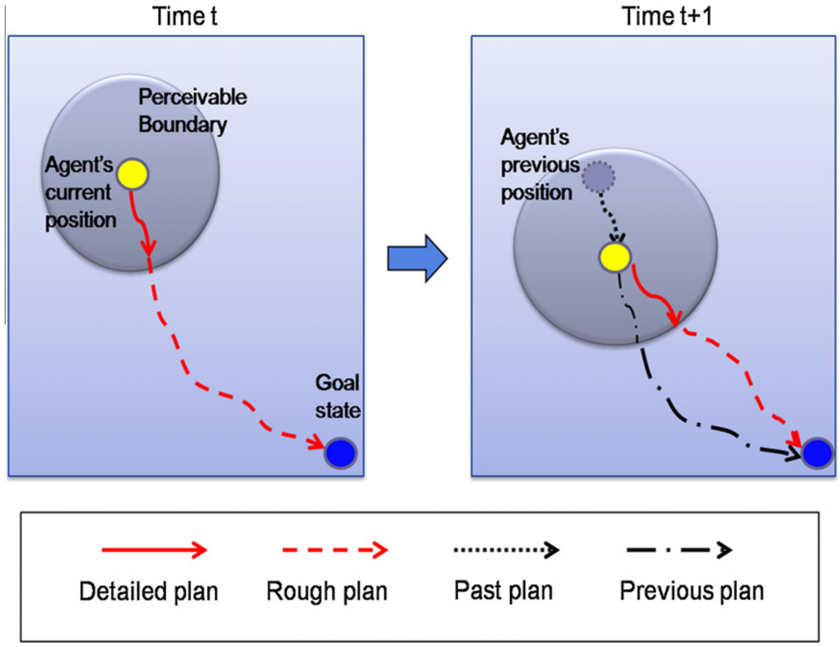



**Fig. 6.** Evolution of human action plan according to the movement of the perceivable boundary.

cell's. On the other hand, the Dynamic Floor Field Indicator (DFFI) $N_d$ is a value assigned to each cell within a perceivable boundary and is obtained from the system's dynamic human perceptual elements, such as obstacles or fires. Each cell occupied by a fire or load (or obstacle) is given very high floor field indicator values, ensuring that evacuees will never attempt to occupy one of them. For example, if a fire is propagated to a cell, the DFFI values of the cell and its neighboring cells are $N_d$(*fire*) = 99, and $N_d$(*neighboring cells of the fire*) = 50, respectively. If a cell is occupied by a load, the value is $N_d$(*load*) = 50.

The DFFI is formally represented and embedded in the simulation model as follows:

(i) An affordance (occupy-ability or move-ability of the cell) of cell (*i*,*j*) is represented as $\text{affordance}_{(i,j)}$.
(ii) If there exist affordance in the cell, $\text{affordance}_{(i,j)} = 1$, if not exist, $\text{affordance}_{(i,j)} = 0$.
(iii) $N_d(\text{Queue})_{(i,j)} = w_{\text{queue}}\ (1\text{-affordance}_{(i,j)})$, where $w_{\text{queue}}$ is weight value which is predefined for each queue type by modeler.
  a. $N_d(\text{load})_{(i,j)} = w_{\text{load}}\ (1\text{-affordance}_{(i,j)})$
  b. $N_d(\text{fire})_{(i,j)} = w_{\text{fire}}\ (1\text{-affordance}_{(i,j)})$
  c. $N_d(\text{neighboring cells of the fire})_{(i\pm1,j\pm1)} = w_{\text{fire\_neighbor}}\ (1\text{-affordance}_{(i,j)})$

Once each cell in the layout is assigned its values of $N_s$ and $N_d$, the values can be summed in each cell; the result is the Adjusted Floor Field Indicator (AFFI). The concept of AFFI is depicted in Fig. 7. The AFFIs are used as basic information for generating the plans for human movement towards the exit, to be explained in detail in the following section.

### *4.4. The planning algorithm*

The evacuee decides his or her movement to the next position based on his or her objective-seeking behavior in the system, composed of conditions and goals. An exemplary objective of human behavior is a "safe and quick (conditions) escape to an exit (goal)" in emergency evacuations.

We develop a generic planning algorithm that can be easily applied to generate a human action plan for the affordance-based simulation problem as follow:

*Step 1*: Define current location of a human agent and perceivable boundary (PB).
*Step 2*: The human agent starts evacuating either if fire is perceived in his/her PB or if another evacuee(s) who are now evacuating from the fire situation is observed within the PB. We assume that the evacuees who have perceived fire in the warehouse share the information of fire-occurrence with other agents within the PBs.
*Step 3*: Based on the current information, make an action plan until the final states (goal state) by calling an objective analysis algorithm. If multiple solutions exist, then randomly choose one of them. (It should be noted that the objective analysis algorithm can be developed for each application domain by specifying its characteristics.)

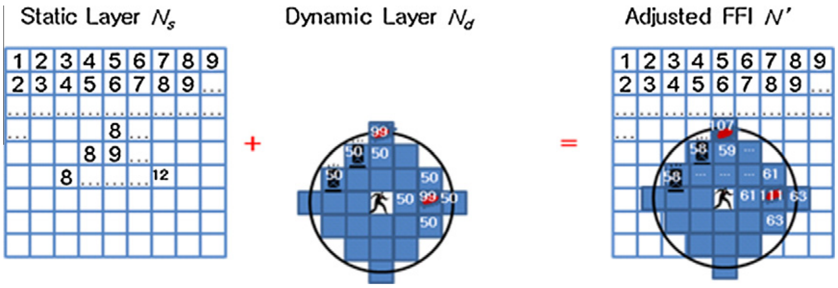



**Fig. 7.** Updating planning information: SFFIs, DFFIs, and AFFIs.

*Step 4*: Move the human agent to the next position on the plan as long as the position is currently affordable. If the human agent reaches the final state (goal state), then stop.
*Step 5*: Update PB and FFIs of cells that newly added to PB. If any state in the plan is not affordable, go to Step 2 and revise the plan. Otherwise, go to Step3.

For generating human movement plans in our WFE problem, it is assumed that the evacuee has prior knowledge of the floor layout and exit locations. Thus, he or she should know how far it is from the current cell to the exit in the storage area. It should be noted that the evacuee can perceive the affordance (occupy-ability or move-ability) of each cell only within his or her perceivable boundary. As illustrated in Fig. 8, the evacuee decides which cell is going to be his or her next position based on the minimum cost analysis: the evacuee will move to the next cell with the minimum total cost value of AFFIs for cells within the planned route.

The plan for evacuee movement is generated from the following planning algorithm:

*Step 1*: Define the current location of an evacuee and perceivable boundary (PB).
*Step 2*: The evacuee starts moving if either fire is perceived in his/her PB or another agent who has perceived fire is located within the PB.
*Step 3*: Based on the current information, make a movement plan (route) within PB until reaching the final state (exit) by calling the minimum cost analysis algorithm. If multiple solutions exist, then randomly choose one of them.
*Step 4*: Move the evacuee to the next cell on the plan as long as the cell is currently affordable. If the evacuee reaches the exit, then stop.
*Step 5*: Update the PB and FFIs of cells newly added to the PB. If any cell in the plan is not affordable, go to Step 2 and revise the plan. Otherwise, go to Step 3.where the minimum cost analysis algorithm is;
*Step A*: Let the current location of an evacuee = $(i,j)$
*Step B3–2*: For the current location $(i,j)$, find a route that is a series of cells satisfying the condition of

$$\min\left\{\sum_{|p|+|q|=1}^{n} N_(i+p,j+q)'\right\},$$

where integer $p, q \in \{0, \pm1, \pm2, \ldots, \pm n\}$, $n$ is the number of cells on a route within PB, which means the radius of the PB, $N'(i,j)$ is adjusted FFI of cell $(i,j)$,
*Step C3*: A cycle or dead end in the route is eliminated through the following; If a cell $(i+p,j+q)$ where $p+q=n$ is visited twice, increase the FFI of cell $(i+p,j+q)$ where $p+q=n-1$ by 5 and find a new route from the initial location $(i,j)$ by repeating Step B.

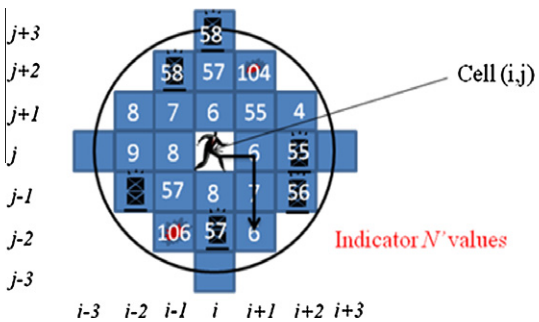



**Fig. 8.** Evacuee movement based on the minimum cost analysis.

## 5. Illustrative example and implementation for verification and demonstration

To verify the applicability of the proposed framework of the affordance-based simulation, perception-based human actions are formalized into a simulation model in the forms of an affordance-based FSA model, agent models, and human action plan for the warehouse fire evacuation simulation. The simulation model is implemented using AnyLogic© software (using an agent-based simulation module). In the simulation model, each evacuee is represented as a human agent, and fire is represented as an environmental agent. Continuous time is turned into discrete time steps, unit times for the simulation. The mean velocity of evacuees is around 2 m/s [37], so that, if we set the time step $\Delta t$ to 0.4 s, human agents move at 0.8 m per time step in average. The mean velocity of fire propagation is assumed to be 0.4 m/s. Thus, a fire broken out in a cell can be propagated into its adjacent cells every five time steps on average. Therefore, the dynamics of the warehouse can be implemented by its floor layout, the dynamic interaction between human agents, and the fire propagating agents in the warehouse.

Once a human agent has developed a goal and plan after finding a fire, he/she will try to move along the route in the plan by checking the action possibilities with respect to the floor layout and the current conditions of fire propagation in the PB of the warehouse. To perform this behavior, each human agent perceives whether its adjacent lots provide it with the affordance, "is-move-able," for the human agent. In this warehouse evacuation problem, the human action taken to evacuate the space is associated with the affordance of "move-ability for an evacuee to an adjacent lot" and the accompanying effectivity of the evacuee's "capability to move to an adjacent lot."

### 5.1. Initial simulation result

The behaviors of agents (human agent of an evacuee and environmental agent of a fire) in response to state transitions concerning the environments (e.g., a fire occurrence) and the human agents (e.g., taking action toward a goal) are described using a state chart in Fig. 9. The agent events are modeled via a sequence of transitions from one state to another. Once an evacuee agent perceives a fire in the perceivable boundary, the agent of the evacuee generates its evacuation plan in consideration of the exit location and floor layout. The human then starts to evacuate from the fire if the agent has the capability (effectivity) to move to a next cell with the affordance to be occupy-able by the evacuee. At the same time, the fire agent propagates based on its predefined transition rule.

Fig. 10 depicts an evolution of the WFE simulation model over time involving 20 × 20 cells, two evacuees, and one exit in the middle of the right side (marked with grey rectangles). The stocks are marked with dark circles, and fire is spread out in the middle of the warehouse. It also depicts the changes in the dynamic floor field indicator over time as a fire propagates into the agent's perceivable boundary. The constructed simulation models can be used to test the impact of various factors (e.g., the number of exits, the number of evacuees, and the size of the warehouse) on the evacuation performance.

The setting for the simulation (such as the layout of warehouse, locations of exits, the number of workers, initial positions of workers, and the initial position of the fire) is defined in a Microsoft Excel file, which is read by AnyLogic© to generate the simulation environment. This allows us to change simulation settings in automatic and interactive ways.

### 5.2. Sample simulation study: Impacts of the position of exits and the number of evacuees

In this section, the impact of the positions of exits and the number of evacuees is analyzed using the constructed WFE simulation model. To test the evacuation performance with regard to the positions of exits and number of evacuees, the

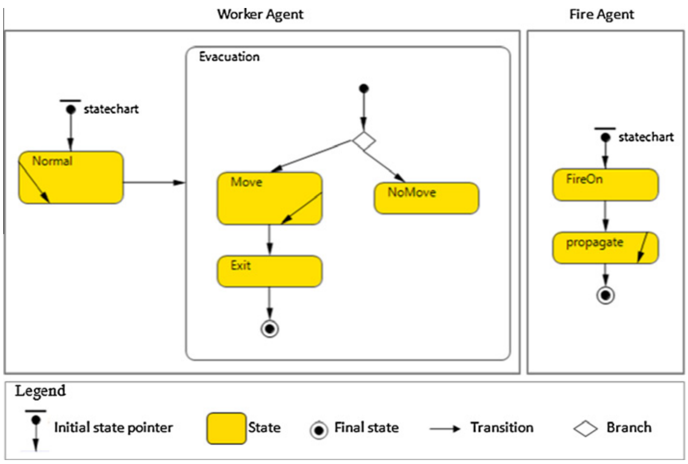



**Fig. 9.** State charts for behaviors of a worker agent and a fire agent.

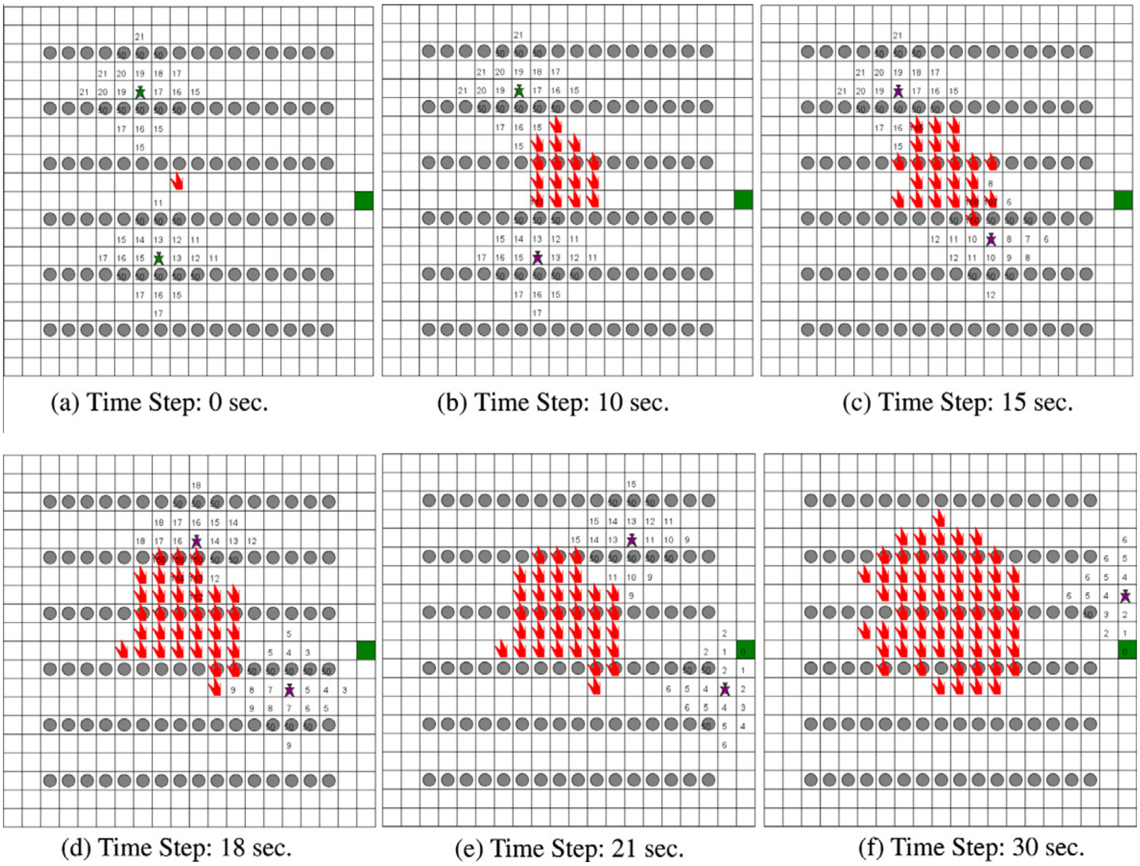



**Fig. 10.** Snapshots of an evolution of the WFE simulation model.

layout of 50 × 50 (2500) cells is modeled as shown in Fig. 11. Six different cases are considered: (1) with one exit (marked with grey rectangles) in the center of the right side and 10 evacuees (Fig. 11a); (2) with one exits in the centers of both sides and 50 evacuees (Fig. 11b); (3) with one exit in the center of the right side and 100 evacuees (Fig. 11c); (4) with two exits in the centers of both sides and 10 evacuees (Fig. 11d); (5) with two exits in the centers of both sides and 50 evacuees (Fig. 11e); and (6) with two exits in the centers of both sides and 100 evacuees (Fig. 11f). The evacuees in the WFE simulation model are initially randomly positioned. A fire is assumed to have broken out from the center of the warehouse and to be propagating to the adjacent cells randomly (with 50% chances). For each test case in Fig. 11, the simulation model was executed in 100 replications; the evacuation time for evacuees and the number of evacuees who fail to evacuate from the system were measured. Table 1 shows the 95% confidence intervals for the metrics (the average evacuation times and the probability of failing to evacuate in the WFE) and their analysis results.

The simulation data were statistically analyzed using MINITAB®. Both the number of exits and the number of evacuees were found to be significant factors with respect to the average evacuation times for evacuees, as shown in Fig. 12c, because the *p*-values of both the number of exits and the number of evacuees are small (<0.05) in 95% CI from the *F*-ratio, while the interaction between the number of exits and the number of evacuees seems to be not significant.

However, when we check the statistical results shown in Table 1 and Fig. 12, more exits seems to make evacuees take longer time to escape from the fire unlike common senses. The reason can be found in that the average evacuation time is meaningful only for the evacuees who successfully run away from the fire situation. The evacuation time for evacuees who could not escape from the fire in the system was not counted, meaning that the average evacuation time is irrelevant to measurements of the WFE system's safety. Moreover, the $R^2$ value of this ANOVA result is also lower than 20%, meaning that the statistical model cannot sufficiently explain the data. The casualty rate (the rate of evacuees who could not escape the fire) of the system should therefore be considered a more important one in analyses of the impact of the warehouse layout and the initial size of evacuees in the system as following equation:

$$\text{Casualty rate} = \frac{\text{the number of evacuees who could not escape from the fire}}{\text{the number of initial evacuees at the starting of the simulation}} \tag{1}$$

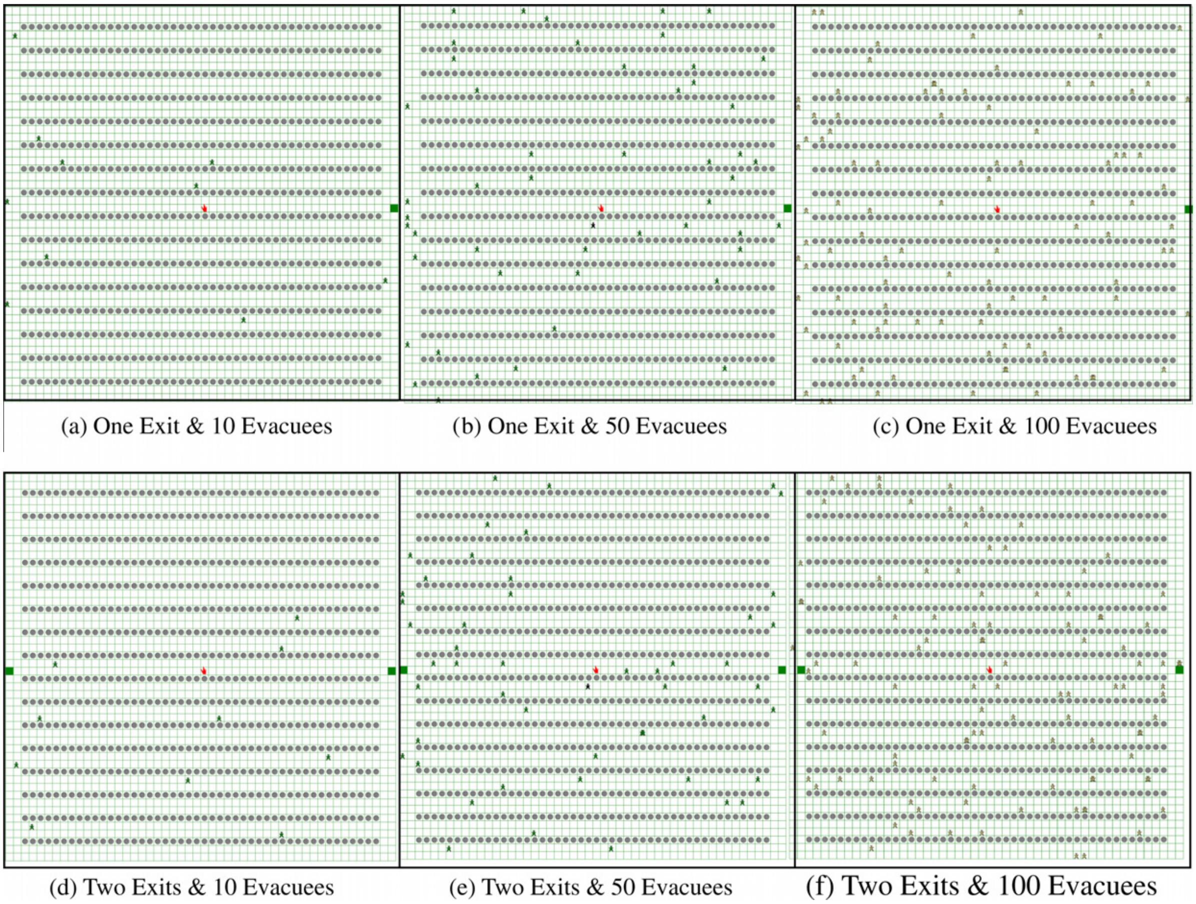
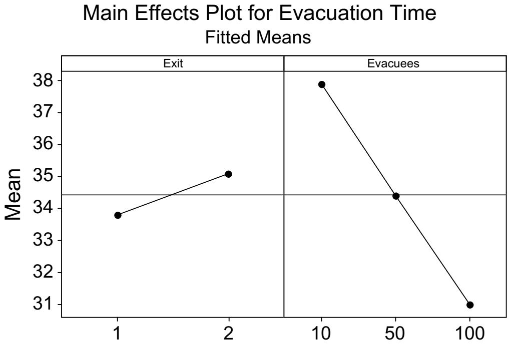



**Fig. 11.** 50 × 50 WFE simulation models with different # of exits and # of evacuees.

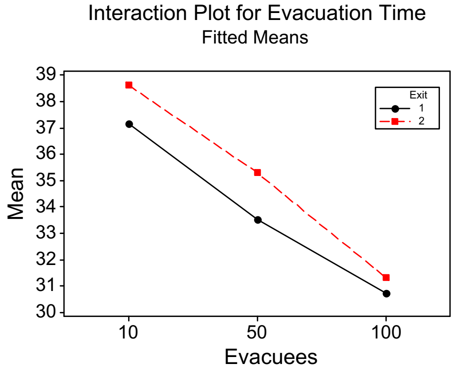
**Table 1**
95% Confidence interval of the average evacuation time and the probability of failing to evacuate.

| | Case A: One exit/ 10 evacuees | Case B: One exit/ 50 evacuees | Case C: One exit/ 100 evacuees | Case D: Two exits/10 evacuees | Case E: Two exits/50 evacuees | Case F: Two exits/ 100 evacuees |
|---|---|---|---|---|---|---|
| 95% CI of avg. evacuation time (STDEV) | 36.03 (10.62) | 33.51 (5.16) | 30.72 (3.15) | 39.36 (6.23) | 35.30 (4.48) | 31.31 (2.95) |
| Probability of failing to evacuate (Casualty rate) | 64.6% | 54.7% | 50.6% | 36.5% | 24.7% | 18.6% |

Concerning the casualty rate (the average percentage of people caught by the fire) as the dependent variable, both the number of exits (the warehouse layout) and the number of evacuees are also analyzed as significant factors, as their *p*-values are less than 0.005, and the $R^2$ value of the ANOVA model is getting high (91.91%), as shown in Fig. 13c). As the number of exits and of evacuees in the system increases, the evacuee survival rate increases in Table 1. More exits would help evacuees escape from a fire more easily because they are supposed to decrease the average FFIs of each agent by reducing the distance from an exit to an agent. When varying the number of exits in the system, overall layout of the warehouse and the evacuation routes of evacuees are subject to be changed as well. The independent variable of 'the number of exits' cannot be considered as continuous variable which can be counted and expected to have the optimal value, different from the number of evacuees. Thus, we can say that the layout of the exits, rather than the number of exits, should be a critical factor for changing their evacuation behaviors. In case of the number of evacuees, the larger number of human agents in the system reduced the casualty rate. That is because the larger number of human agents can provide human agents more opportunities to perceive a fire-occurrence earlier because agents are assumed to recognize each other within their PBs, and they can start evacuating only after perceiving the movements of other agents. However, we suspect that if the number of human agents increases over the threshold, the casualty rate might also get larger due to congestion effect. In the residual test for the average percentage of people in the fire (as shown in Fig. 14), we confirm that the data are well modeled from normal distribution.




(a) Main effects plot




(b) Interaction plot

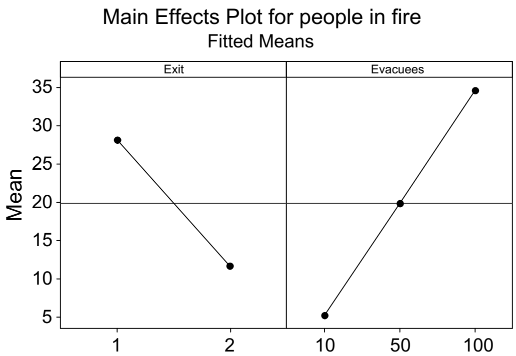
**Two-way ANOVA: Evacuation Time versus Exit, Evacuees**

| Source | DF | SS | MS | F | P |
|---|---|---|---|---|---|
| Exit | 1 | 248.6 | 248.59 | 6.10 | 0.014 |
| Evacuees | 2 | 4720.9 | 2360.43 | 57.94 | 0.000 |
| Interaction | 2 | 38.4 | 19.18 | 0.47 | 0.625 |
| Error | 594 | 24200.9 | 40.74 | | |
| Total | 599 | 29208.8 | | | |

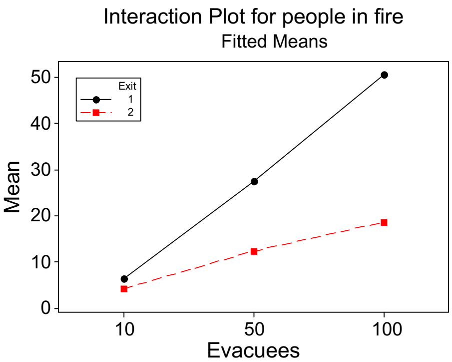
S = 6.383 R-Sq = 17.14% R-Sq(adj) = 16.45%

(c) ANOVA result

**Fig. 12.** Effects of the number of exits and of evacuees on the average evacuation time.




(a) Main effects plot




(b) Interaction plot

**Two-way ANOVA: people in fire versus Exit, Evacuees**

| Source | DF | SS | MS | F | P |
|---|---|---|---|---|---|
| Exit | 1 | 40574 | 40573.9 | 1839.79 | 0.000 |
| Evacuees | 2 | 85909 | 42954.6 | 1947.74 | 0.000 |
| Interaction | 2 | 22264 | 11132.2 | 504.78 | 0.000 |
| Error | 594 | 13100 | 22.1 | | |
| Total | 599 | 161847 | | | |

S = 4.696 R-Sq = 91.91% R-Sq(adj) = 91.84%

(c) ANOVA results

**Fig. 13.** Effects of the number of exits and of evacuees on the average percentage of people in the fire.

From the above simulation results, we have verified that the affordance-based agent model works for simulating human fire evacuation behavior. When considering complex human decision-making/action-taking, many physical and psychological factors must be considered at the mathematical modeling stage. This study proposes a new simulation approach to evacuation problems in emergency situations using an affordance-based agent model, as implemented though a simple WFE problem. Although our WFE example uses simple simulation cases, its fire propagation and agents' evacuation processes are independently modeled and simultaneously run to accurately calculate the behaviors of all agents in the system by

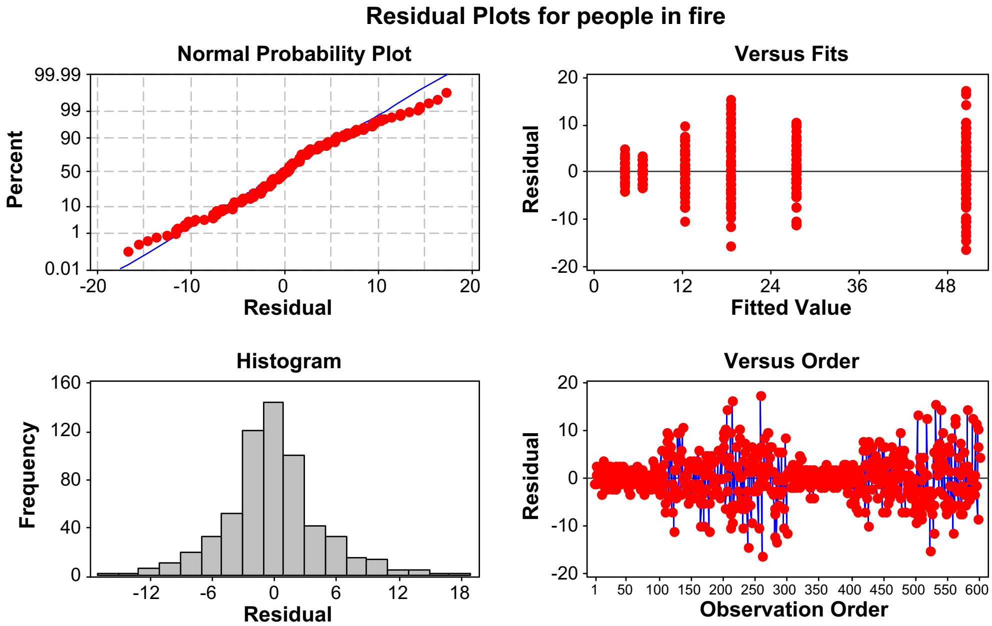



**Fig. 14.** Residual analysis of the simulation data.

sharing affordance–effectivity conditions in the spatial–temporal dimensions. Thus, the proposed agent-based model can simulate a number of dynamic agents' behaviors quickly and effectively by defining dual relationships between the environmental properties of affordances and the agents' capabilities of effectivities.

## 6. Conclusions

Emergency evacuations from disastrous situations represent a kind of complex human-environment system in which humans dynamically interact with environmental elements. In this research, we have explored a novel simulation methodology for emergency evacuation situations that incorporates the ecological concept of affordances. The modeling and simulation architecture proposed in this paper provides powerful capabilities for planning, scheduling, and executing human actions in prospective control over the simulation because it incorporates perception-based human decision-making processes into the discrete event-based system structures. We have demonstrated the applicability of the proposed framework by a simulation study using the illustrative example of the warehouse fire evacuation problem. The simulation capabilities of the proposed evacuation application have been demonstrated by being tested through simulation performances using different space layouts and numbers of system agents. The simulation model presented in this paper is agent-based as well as perception-based. It allows a human agent to make decisions based on perceived affordance given by surrounding environment. Since the proposed framework interprets human actions as a set of perceivable action opportunities, it can dramatically reduce the complexity of human behavior (for example, in the evacuation model, agents do not have many alternatives, they can only decide which cell they should occupy next) and give a new perspective of simulating human behaviors in systems. The human agent (evacuee) in the demonstrated simulation model has its own algorithm, the "minimum cost analysis algorithm," which generates evacuation plans based on both prior knowledge of the floor layout and what it perceives in the perceivable boundary. The static and dynamic floor field indicators are applied to represent the human planning algorithm, and they are summed up to create the AFFIs indicating human behavioral patterns in the space. The proposed agent model can regenerate evacuation plans whenever its perceivable surrounding environments change. This simulates realistic human behaviors, which are dependent on perception-based decision-making, as asserted by ecological psychologists. We have implemented our simulation framework using the AnyLogic© simulation package. Our WFE problem was developed using FSA (cellular automata), a popular approach to system representation, with computability and scalability.

The proposed framework is applicable to other problem domains [9,10]. Kim et al. provide manufacturing control and highway driving examples using affordance-based FSA formalism in [9,10], respectively. The examples developed using FSA formalism have computability and scalability [38]. The environmental model offers information on dimensional states, while the agent models indicate individual states under specific conditions. The combined FSA model should be able to simulate highly complex situations by including environmental and multiple agent dynamics simultaneously because the state transitions are all under the pre-defined conditions described in the FSA model. This will give us a systematic procedure by which to build affordance-based simulation models in complex human-involved systems for the simulation of human actions and the design of human-involved systems. While we have focused on the framework and human perception (a major function) in this work, the underlying assumption in this paper is that the agent-based simulation framework considers only perception-based action, which implies the ecological properties of affordance and effectivity, rather than the social factors that might affect human decision making.

However, many problems remain to be overcome. The proposed model lacks the reality of an actual fire situation and should thus be used to model more realistic scenarios. Our warehouse layout, for example, is much simpler than actual warehouse layouts. In addition, although we suppose that the evacuees within each others' PBs can affect each other, this does not necessarily mean that the social behaviors of the human agents have all been modeled. Social factors such as gender, race, age, and physical attributes were not considered in this research. We will consider these human social attributes (e.g., social psychology, emotions, cultures, and knowledge levels) in future research. We shall also have to validate the simulation results through human experiments in a suitable task environment (e.g., in a virtual reality).

Using the proposed modeling and simulation framework for a variety of applications (such as pedestrian moving and building evacuation) will further the breadth and depth of the human-integrated systems and simulation areas containing complex and multiple human activities. The deliverables in this research are expected to merge system engineering technologies with human factors and generate a novel informational technology that can be used for future disaster simulations and homeland security management.

## Acknowledgement

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